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Consumer confidence in Europe: United in diversity?

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Abstract

The ongoing unification taking place in the European political scene, along with recent advances in consumer mobility and communication technology, raises the question of whether the European Union can be treated as a single market to exploit potential synergy effects from pan-European marketing strategies. Previous research, which mostly used domain-specific segmentation bases, has resulted in mixed conclusions.

In this paper, a more general segmentation basis is adopted, as we consider the homogeneity in the European countries' Consumer Confidence Indicators. Moreover, rather than analyzing more traditional static similarity measures, we adopt the concepts of dynamic correlation and cohesion between countries. The short-run fluctuations in consumer confidence are found to be largely country specific. A myopic focus on these fluctuations may inspire management to adopt multicountry strategies, forgoing the potential longer-run benefits from more standardized marketing strategies. Indeed, the Consumer Confidence Indicators become much more homogeneous as the planning horizon is extended. Moreover, this homogeneity is inversely related to the economic and cultural distance among the various member states. Hence, pan-regional rather than pan-European strategies are called for.

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Keywords: Consumer confidence; Dynamic correlation; European unification; International segmentation

1. Introduction

Western European countries have a longstanding, post-WW II tradition of unification, as reflected in agreements to establish the Benelux, the European Free Trade Association, the European Union, and, eventually, the European Monetary Union (Tellis, Stremersch, & Yin, 2003; see also McDonald & Dearden, 2005 for an extensive discussion). In addition, the increasing mobility, education, and sophistication of consumers, the growing availability of various distance-spanning technologies, and the emergence of pan-European media have contributed to the perception that distance has become irrelevant within Europe (Mahajan & Muller, 1994; Tellis et al., 2003; ter Hofstede, Steenkamp, & Wedel, 1999). All these factors suggest that the different member states could be treated as a single market, making a unified, pan-European marketing strategy appropriate

(Steenkamp & ter Hofstede, 2002). Such a strategy is attractive not only because of the economies of scale that European standardization may leverage (Yip, 1995) but also because of the possibility to coordinate competitive and strategic moves or exploit the emergence of global retailers (Özsomer & Simonin, 2004). However, we could also argue that European countries continue to differ considerably from one another economically (The Economist, 1999), in terms of laws and regulations (The European Voice, 2001), and (some may argue, especially) as far as cultural identity is concerned (Kraus, 2003; Rosenberger, 2004). If countries continue to possess predominantly distinct market identities, multi-domestic, rather than pan-European, marketing strategies are called for.¹

Previous research on the “unity” of the European market has provided mixed evidence. One stream of research favors pan-European marketing strategies, while other studies identify

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¹ In some instances, a compromise between standardization and local flexibility may be used, which has been referred to as a “glocal” strategy (Yip, 1995). One then standardizes some parts (e.g., production, organization, technologies) while customizing others (e.g., product features, communication).

substantial differences among various European countries, providing support for multi-domestic or multi-regional strategies. One reason for these conflicting findings could be that most aforementioned studies consider *domain-specific* segmentation bases (notable exceptions are Kamakura, Novak, Steenkamp, & Verhallen, 1994; Wedel, ter Hofstede, & Steenkamp, 1998). Although such insights are very useful to the particular industry, they are less likely to generalize to other settings (Steenkamp & ter Hofstede, 2002). We adopt a more general measure of consumer homogeneity/heterogeneity in Europe that is less dependent on the specific domain of study. Our point of departure is the Consumer Confidence Indicator (CCI) of the various European countries. As we will discuss in more detail in Section 2, the CCI permeates many purchase decisions consumers face (Allenby, Jen, & Leone, 1996). As such, it is a prime candidate for studying, in more general terms, the extent of homogeneity in consumers' attitudes and buying behavior across countries.

Moreover, whereas previous studies adopted *static* similarity measures, we analyze the degree of homogeneity in European consumers' CCI *dynamically*, using the frequency-based concepts of *dynamic correlation* and *cohesion* (Croux, Forni, & Reichlin, 2001). There is increasing evidence that the relationship among economic variables may vary, in direction and/or importance, over different planning horizons where every planning horizon corresponds to a different *periodicity* (Bronnenberg, Mela, & Boulding, 2006). Our aim is to disentangle the temporary or shorter-run fluctuations in consumer confidence from the longer-run changes and to investigate how these short- and long-run variations differ across countries. It may well be that country-specific disturbances dampen the extent of short-run homogeneity (more precisely, the homogeneity across countries in short-run fluctuations in consumer confidence), while more homogeneous patterns emerge as the planning horizon is extended. If this is indeed the case, the feasibility/attractiveness of pan-European marketing strategies depends on the planning horizon that is envisioned. A myopic (short-run) focus may then inspire managers to adopt a multi-country strategy, forgoing the potential longer-run benefits of a pan-regional, or even pan-European, strategy.

To investigate this possibility, we address the following research questions. First, to what extent are Consumer Confidence Indicators homogeneous across all member states of the European Union? How does this degree of homogeneity differ across different planning horizons, and how does it compare with the homogeneity across the different regions of the United States? Second, if there is considerable heterogeneity across the member states, do certain regions (segments) exist that are more homogeneous? Third, to what extent can geographical, cultural, and economic distance help explain the observed heterogeneity, if any, in the various countries' CCI?

The remainder of the paper is organized as follows: in the next section, we review previous research on European segmentation; in Section 3, we formally define the concepts of dynamic correlation and cohesion, which are derived in the spectral domain; in Section 4, we discuss the data, and then present empirical findings in Section 5. Managerial implications and conclusions are drawn in Section 6.

2. European segmentation

The segmentation of the European market has been investigated in numerous previous studies. Table 1 positions our research relative to this earlier work along three key dimensions: (i) the domain-specific versus general nature of the segmentation basis, (ii) the static versus dynamic nature of the segmentation method, and (iii) the level of analysis (country versus consumer level).

2.1. Nature of the segmentation basis

As shown in the final column of Table 1, previous research on the homogeneity of the European market has resulted in mixed conclusions. One stream of research supports the idea of pan-European marketing strategies. For example, ter Hofstede et al. (1999) identify a pan-European consumer segment in yoghurt consumption motives. According to Gielens and Dekimpe (2001), neither cultural nor geographical proximity affects the long-run performance of European retailers' international operations. In their study of the drivers of consumer acceptance of new packaged goods, Gielens and Steenkamp (2004) report that various consumer variables work in the same direction in four key European countries (France, Germany, Spain, and the United Kingdom), which suggests that these variables offer a basis for horizontal market segmentation across borders. Evidence of cross-national segments is also found in ter Hofstede, Wedel, and Steenkamp (2002) and Wedel et al. (1998), among others.

Still, many studies identify substantial differences between various European countries, providing support for multi-domestic strategies. Geographical, economic, and/or cultural distances are found to remain key drivers of market heterogeneity in Europe. Bijmolt, Paas, and Vermunt (2004), for instance, find that European countries differ considerably in financial product ownership. On the basis of that dimension, they partition the European market into seven segments. Interestingly, their division is closely linked with geographical proximity. In terms of food culture, Askegaard and Madsen (1998) find Europe to be heterogeneous across its geographical and language borders. Finally, ter Hofstede et al. (2002) and Wedel et al. (1998) identify both country-specific and cross-country segments.

In the diffusion literature, Tellis et al. (2003) report substantially different times-to-takeoff for new products in Europe, partially related to cultural distance. Stremersch and Tellis (2004) discover significant differences in the European growth rates of consumer durables and find these differences to be mainly related to economic distance. Finally, Kumar, Ganesh, and Echambadi (1998) conclude that geographical, economic, and cultural distance helps explain diffusion similarities across Europe.

In summary, research on the unity of the European market offers mixed conclusions in terms of the presence/absence of cross-country segments, the number and composition of such segments, and the relative importance of various distance measures in describing them. One reason could be that most aforementioned studies consider *domain-specific* segmentation bases covering specific characteristics such as yoghurt

Table 1
Overview of previous European market segmentation studies

Segmentation							
Study	Sample (# European countries)		Segmentation basis		Segmentation level	Segmentation level	Key findings
Askegaard and Madsen (1998)	15	Domain- specific	Food culture	Static	Factor and cluster analysis	Consumer	12 country-(or language-) specific segments
Bijmolt et al. (2004)	15	Domain- specific	Financial-product ownership	Static	Multi-level latent-class analysis	Country+ consumer	4 cross-national and 3 country- specific segments
Boote (1983)	3	General	Instrumental values	Static	Q-factor analysis	Consumer	1 cross-national and 3 country- specific segments
Gielens and Dekimpe (2001)	24	Domain- specific	Long-run performance of retailers	Static	Gompertz model	Consumer	No moderating role of cultural or geographical proximity
Gielens and Steenkamp (2004)	4	Domain- specific	Drivers of new packaged goods’ acceptance	Static	Poisson regression model	Country+ consumer	Same drivers across countries
Kale (1995)	17	General	Hofstede’s national– culture dimensions	Static	Cluster analysis	Country	3 cross-national segments
Kamakura et al. (1994)	3	General	Instrumental and terminal consumers’ values	Static	Clusterwise rank logit model	Consumer	5 cross-national segments, with a strong national orientation
Kumar et al. (1994)	11	Domain- specific	Multicriteria market potential (in the machinery industry	Static	Augmented weighted Tchebycheff procedure	Country	Different segments depending on managers’ preferences
Kumar et al. (1998)	14	Domain- specific	Bass diffusion parameters	Static	Cluster analysis	Country	Different segments across countries, related to geographical, cultural and economic distance
Putsis et al. (1997)	10	Domain- specific	Rates of internal/external contacts	Static	Mixing diffusion model	Country	Highly segmented across countries with strong cross-national influences
Steenkamp (2001)	11	General	Factor scores on the Hofstede and Schwartz national-culture values	Static	Two-stage cluster analysis (Ward’s and K-means)	Country	3 cross-national segments (for Europe)
Stremersch and Tellis (2004)	16	Domain- specific	Growth rates of new products	Static	Parametric hazard model	Country	Significant explicative role of economic distance
Tellis et al. (2003)	16	Domain- specific	Time-to-takeoff of new products	Static	Parametric hazard model	Country	Significant explicative role of cultural values
ter Hofstede et al. (1999)	11	Domain- specific	Means-end chain data on yoghurt consumption	Static	Mixture model accounting for within-and between- country heterogeneity	Consumer	4 cross-national segments, including one pan-European
ter Hofstede et al. (2002)	7	Domain- specific	Store image in meat retailing	Static	Hierarchical Bayes model for spatial dependence	Consumer	3 cross-national and 2 mainly country-specific segments
Vandermerwe and L’Huillier (1989)	18	General	Socio-geographic variables	Static	Cluster analysis	Country	6 cross-national segments
Wedel et al. (1998)	6	General	LOV values	Static	Mixture model accounting for various sampling designs	Consumer	5 cross-national segments, including 2 pan-European and 1 country- specific
Present study	14	General	The Consumer Confidence Indicators	Dynamic	Spectral analysis of co- movement	Country	National segments in the short run, vs. pan-regional segments in the longer run

consumption, financial product ownership, or the takeoff of consumer durables. In line with Boote (1983), Kamakura et al. (1994), Steenkamp (2001), Vandermerwe and L'Huillier (1989), Wedel et al. (1998), among others, we adopt a more general segmentation basis. General segmentation bases are independent of the domain in question (Steenkamp & ter Hofstede, 2002) and particularly useful when trying to identify more general patterns

applicable to multiple settings. From a managerial point of view, such patterns are of particular interest to firms offering multiple product categories (ter Hofstede, 1999).

The general segmentation basis adopted in this study is the Consumer Confidence Indicator (CCI) of various countries. The European CCI and its U.S. counterpart, the Index of Consumer Sentiment (ICS), have been found to be leading indicators of

consumers' willingness to buy, as well as expenditures on durables (Burch & Gordon, 1984; Throop, 1992), non-durables (Mueller, 1963), household goods and motor vehicles (Adams, 1965; Friend & Adams, 1964), and fashion merchandise (Allenby et al., 1996), among others. In addition, they have been found useful in forecasting recession periods (Batchelor & Dua, 1998) and can be used as a proxy for consumer sunspots, such as changes of attitudes (Chauvet & Guo, 2003). Moreover, they affect consumers' propensity to buy private labels (Lamey, Deleersnyder, Dekimpe, & Steenkamp, *in press*). Consumers' confidence in the economy is also closely linked to their price sensitivity (Estelami, Lehmann, & Holden, 2001), which has been found to be an actionable source for horizontal segmentation in global markets (Bolton & Myers, 2003). Because the CCI permeates many purchase decisions consumers face (Allenby et al., 1996), it is a prime candidate to assess in more general terms the extent of homogeneity among European countries. These publicly available data are collected consistently by the European Commission over multiple countries and over a long time span. Moreover, as the construct is conceptually similar to the American ICS, a formal comparison with the United States, which has a much longer history of unification, becomes feasible.

2.2. Static versus dynamic segmentation

As shown in Table 1, previous research is based on *static* similarity measures. Bijmolt et al. (2004), for example, partition the European market in terms of a one-shot measure of product ownership; ter Hofstede et al. (1999) segment means–end relations identified in a single data-collection wave; and Askegaard and Madsen's (1998) analysis of European food cultures is based on lifestyle survey data collected at a single point in time. Although international diffusion-based studies consider multiple time points, their main focus lies in subsequently explaining the cross-sectional variation in a single summary statistic, such as the time-to-takeoff (Tellis et al., 2003), average growth rate (Stremersch & Tellis, 2004), or asymptotic value (Gielens & Dekimpe, 2001).

However, there is increasing evidence that the relationship between economic variables may vary, in direction and/or importance, over different planning horizons (e.g., Baxter, 1994). In marketing, numerous studies have demonstrated that the short- and long-run effectiveness of marketing mix expenditures may differ considerably (e.g., Nijs, Dekimpe, Steenkamp, & Hanssens, 2001; Pauwels, Hanssens, & Siddarth, 2002). Similarly, Bronnenberg et al. (2006) find that the nature of competitive interactions in the U.S. beer market differs for different planning cycles. When focusing on the short-run (weekly, biweekly) fluctuations in the prices of Budweiser and Miller, cooperative behavior is found, which they interpret as retailers preferring to promote the brands in alternate weeks. However, they also identify longer-term movements in these brands' regular prices. These price changes, which occurred approximately every 25 weeks, were found to be positively correlated, suggesting competitive behavior. Deleersnyder, Dekimpe, and Leeflang (2004), in turn, find that the link

between aggregate advertising and gross national product (GNP) over business-cycle frequencies differs in relationships found in the short and long run. Indirect evidence for the relevance of this time dependence in assessing the usefulness of pan-European marketing strategies is provided in the combined studies of Tellis et al. (2003) and Stremersch and Tellis (2004). Using the same European diffusion data, they find different factors (cultural and economic, respectively) drive the time-to-takeoff and subsequent growth rate of consumer durables. Hence, depending on the planning stage, different country segments emerge.

In this paper, we adopt a dynamic correlation measure to describe the similarity between different countries' Consumer Confidence Indicator. Using recently developed spectral time-series techniques, we assess to what extent the CCI series' fluctuations at different frequencies (periodicities) are correlated. Because there is a one-to-one correspondence between these frequencies and the planning horizon (refer to Section 3 for technical details), we can investigate to what extent the homogeneity across different countries changes as the planning horizon is extended.

2.3. Country-versus consumer-based segmentation

Even though some studies on European market segmentation have considered the segmentation of consumers (e.g., Gielens & Steenkamp, 2004; Wedel et al., 1998), most use the country as a basic unit of analysis, as summarized in column 7 of Table 1. Bijmolt et al. (2004) attribute this to the high costs and low availability of international databases, especially when considering, as in our study, multiple countries ($N=14$) with data collected at multiple instances ($T=117$).

Country-level analyses require a meaningful degree of *within-country commonality* and *between-country differences* in consumer confidence. In terms of the within-country commonality, Hofstede (1991, p. 12) argues that nations are the "source of a considerable amount of common mental programming of their citizens," because of the common political, legal, and educational environments they represent. Although this commonality does not imply that countries are fully homogeneous, it suggests the presence of some generalized forces that cause a meaningful amount of within-country commonality (Steenkamp, 2001).

Such generalized forces could refer to general economic conditions (e.g., variations in job vacancies influence Australian consumers' confidence; Roberts & Simon, 2001), the political climate (Vuchelen, 1995 finds a significant link between the outcome of national elections and a country's confidence level), and events that may inspire national pride (e.g., performance in international sporting competitions; see Bolger, Franses, & Antonides, 1999) or cause national sorrow (e.g., the London bombing; The Guardian, 2005). As these generalized forces differ across countries (national elections take place on different dates and government coalitions differ across countries, unemployment levels are not identical, and the performance of national teams in international competitions varies widely), between-country differences in consumer confidence can be expected.

3. Dynamic correlations

3.1. Spectral analysis

Most currently available time-series applications in marketing are situated in the time domain (see Dekimpe & Hanssens, 2004, for a recent review). Spectral analysis, situated in the frequency domain and very popular in engineering (e.g., Priestley, 1981), has received much less attention. Early exceptions are Parsons and Henry (1972), Barksdale, Hilliard, and Guffey (1974), and Barksdale, Hilliard, and Ahlund (1975). Parsons and Henry introduce spectral analysis as a diagnostic tool to test the equivalence between actual and predicted sales series. Barksdale et al. (1974) apply spectral tools to study the relationship among advertising expenditures, car factory sales, and new car registrations over different frequencies. Finally, Barksdale et al. (1975) study the link between price changes and quantities of beef at the slaughterhouse level. Short-run changes in price were found to lead to short-run changes in quantity by several months. In contrast, long-run decreases in quantities corresponded to long-run increases in price without time delay.

More recently, Bronnenberg et al. (2006) investigated the nature of competitive price reactions occurring at different frequencies. They found competitors' reactions to short-term

price reductions differ considerably from their reactions to long-run price changes. In the former case, there was clear evidence of cooperative behavior (i.e., the reactions are negatively correlated), whereas competitive behavior prevailed in the longer run (i.e., the correlation is positive). Finally, Deleersnyder, Dekimpe, Sarvary, and Parker (2004) use spectral band-pass filters in their study on the link between durables' diffusion patterns and business-cycle fluctuations, while Lamey et al. (in press) use similar filters to study the link between private-label success and successive expansions and recessions.

A common finding in these studies is that marketing relationships may differ across different frequencies (planning horizons). This distinction led Pauwels et al. (2005) to call for more spectral-based time-series applications in marketing, which could lead to novel insights into a wide variety of substantive marketing problems.

Central to spectral theory is the notion that any time series can be decomposed into an infinite sum of (uncorrelated) cyclical components, each having a different frequency λ . Each frequency λ (ranging between 0 and π) corresponds to a unique planning horizon T , with $T=(2\pi/\lambda)$. In the case of monthly data, a frequency of $\lambda=0.5$ represents a one-year planning horizon (more precisely, 12.56 months), that is, the yearly cyclical component in the time series. The underlying intuition

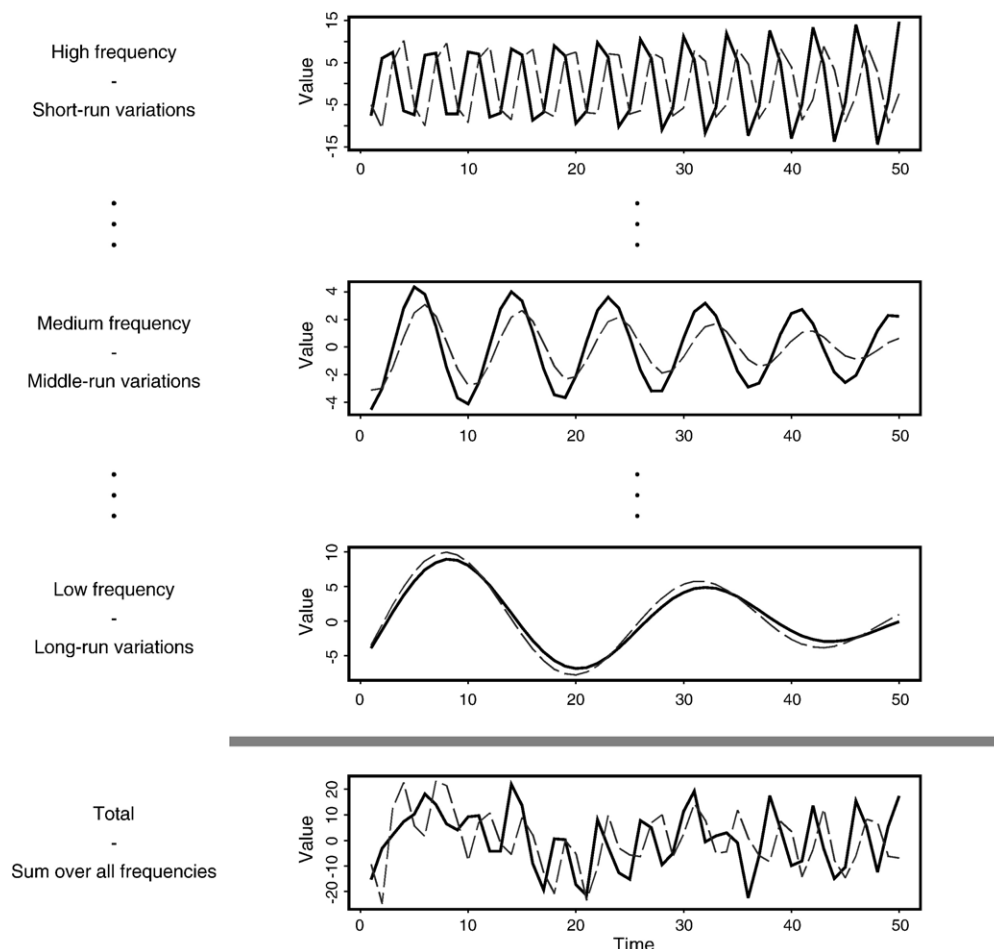


Fig. 1. The decomposition of two time series at different frequencies.

is illustrated in Fig. 1 for two simulated processes (both depicted in the bottom plot). Both series are formed by higher-frequency components (corresponding to shorter-run planning horizons), middle-frequency components (for middle-run planning horizons), and lower-frequency components (for longer-run time horizons). For illustrative purposes, we present in Fig. 1 a typical high-frequency ($\lambda = 1.57$, $T \approx 4$ months), medium-frequency ($\lambda = 0.70$, $T \approx 12$ months), and low-frequency ($\lambda = 0.26$, $T \approx 24$ months) components of both series.

In reality, a time series is composed of an infinite sum of such components that can be isolated through spectral analysis. This isolation makes it possible to study the correlation between two time series at any planning horizon. In Fig. 1, the high-frequency components ($T \approx 4$ months) are quite uncorrelated, with different amplitudes, and they appear out of phase.² The low-frequency components ($T \approx 24$ months), in contrast, are almost perfectly correlated, as their amplitudes are very close, and the series are in phase.

Consider N stationary time series x_1, \dots, x_N , each of length T . In our application, the series represent the first-differenced CCI of the various EU countries. Traditional unit-root tests can be used to test for the stationarity of the various series (e.g., Nijs et al., 2001; Pauwels et al., 2002 for recent marketing applications). Removal of stochastic trends – by first differencing the series – is called for, as this trend otherwise would be treated as part of a very long oscillation, which would swamp the effects of shorter-period fluctuations (Parsons & Henry, 1972). Each stationary series x_i is characterized by a spectral density function, or spectrum $S_{x_i}(\lambda)$, which is defined at each frequency $\lambda \in [0, \pi]$ by

$$S_{x_i}(\lambda) = \frac{1}{\pi} \sum_{k=-\infty}^{+\infty} \gamma_{x_i}(k) e^{-i\lambda k}, \quad (1)$$

with $\gamma_{x_i}(k) = \text{Cov}(x_{i,t}, x_{i,t-k})$, the auto-covariance of x_i at lag k . The area under the spectrum equals the total variance of the time series. The spectrum shows the distribution of the total variance across the frequency band (Chatfield, 1996, p. 96), and $s_{x_i}(\lambda)$ measures the variance of the cyclical component of x_i at frequency λ . As such, the spectrum reveals how much variability in consumer confidence can be attributed to different components, each of which corresponds to different frequencies, ranging from slowly moving to quickly moving components. In turn, the cross-spectrum $S_{x_i x_j}(\lambda)$ characterizes the relationship between two time series x_i and x_j at frequency λ :

$$S_{x_i x_j}(\lambda) = \frac{1}{\pi} \sum_{k=-\infty}^{+\infty} \gamma_{x_i x_j}(k) e^{-i\lambda k} = C_{x_i x_j}(\lambda) + iQ_{x_i x_j}(\lambda), \quad (2)$$

where $C_{x_i x_j}(\lambda)$ is the real part of the cross-spectrum and $Q_{x_i x_j}(\lambda)$ is the imaginary part. Here, $\gamma_{x_i x_j}(k) = \text{Cov}(x_{i,t}, x_{j,t-k})$ represents the cross-covariance between x_i and x_j at lag k . Conceptually, $s_{x_i x_j}(\lambda)$ is a measure of the covariance between the cyclical

components corresponding to the frequency λ of the time series x_i and x_j . The spectra are estimated by first computing the discrete Fourier transform of the time series. The squared modulus of this transform is then smoothed by a weighted moving average, yielding the estimated spectrum.³ Because of the non-parametric nature of this estimation procedure, the number of assumptions is minimal. The only requirement, as indicated previously, is for the series to be stationary.

3.2. Dynamic correlation

The spectral-based dynamic correlation, first discussed in Croux et al. (2001), provides a formal measure of the correlation, or degree of co-movement, between two series x_i and x_j at each individual frequency λ and is given by

$$\rho_{x_i x_j}(\lambda) = \frac{C_{x_i x_j}(\lambda)}{\sqrt{S_{x_i}(\lambda) S_{x_j}(\lambda)}}. \quad (3)$$

This correlation, which ranges between -1 and $+1$, is conceptually similar to the correlation between two series in the time domain. The higher its value, the more similar the fluctuations in consumer confidence at that frequency. However, unlike the (single) static correlation in the time domain, the result is a correlation coefficient that can vary across different frequencies or planning horizons. Other applications of the concept include Carlino and DeFina (2004), Partridge and Rickman (2005), Rua and Nunes (2005), and Sussmuth and Woitek (2004), among others.

Note that prior marketing studies have used the cointegration concept to describe the long-run co-movement between time series (e.g., Franses, Kloek, & Lucas, 1999; Srinivasan, Popkowski Leszczyc, & Bass, 2000). In so doing, they focus on the dynamic correlation at frequency zero between the first-differenced time series, which equals 1 (in absolute value) when both original series are cointegrated (see Croux et al., 2001, for an in-depth discussion). Our dynamic correlation concept is more comprehensive, in that we look at the correlation across the entire frequency band. As discussed previously, the planning horizon is inversely related to the frequency. Hence, the higher (lower) the frequency, the shorter (longer) the planning horizon.

Fig. 2 graphically depicts the estimated dynamic correlation between the aforementioned two simulated series. In line with our discussion of Fig. 1, the lowest frequencies show the highest correlation, implying that the longer-run fluctuations in the series are strongly related and show quite similar patterns. The

² The amplitude of the cyclical components is given by the height of the waves. Waves with the same frequency but whose maxima occur at different instances are said to be *out-of-phase*.

³ The discrete Fourier transform, which establishes the equivalence between the frequency and time domain, provides the decomposition of a discrete time series x over its component frequencies. It is defined as $F(\lambda) = \sum_{t=-\infty}^{+\infty} x_t \exp(-i\lambda t)/\pi$. Because it is too unstable for estimation purposes, we use a smoothed version. In our empirical application, we perform the estimation of the spectra using built-in routines of the S-Plus statistical software package. This software package applies three times the Daniell's smoother to the discrete Fourier transform (see Koopmans, 1995, for more details).

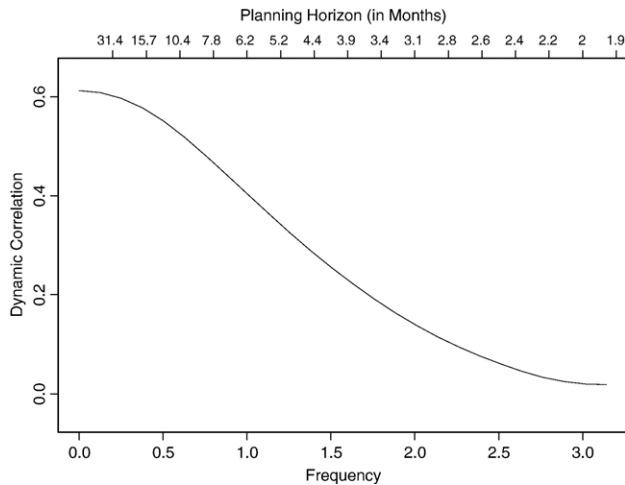


Fig. 2. The dynamic correlation between the simulated series of Fig. 1.

higher frequencies exhibit a much lower correlation, implying that both series are characterized by more idiosyncratic short-run fluctuations. Obviously, this dynamic correlation pattern is more insightful than the single static correlation coefficient of 0.293 between both simulated series.

3.3. Cohesion and cross-cohesion

From a panel of N time series (or countries), we may derive $N(N-1)/2$ possible pairwise dynamic correlations. The higher these correlations, the more homogeneous the respective countries are, in that their customers react in a similar way (in terms of their confidence) to various market disturbances. To obtain an aggregate measure of co-movement within this panel, or part of it, we can compute the *cohesion* (Croux et al., 2001) at frequency λ , denoted by $\text{Coh}(\lambda)$. For $1 < n_1 \leq N$ series, this cohesion is:

$$\text{Coh}(\lambda) = \frac{2}{n_1(n_1 - 1)} \sum_{i < j}^{n_1} \rho_{x_i x_j}(\lambda). \quad (4)$$

Hence, the cohesion is simply the average of all possible pairwise dynamic correlations among a given set of countries that yields an aggregate measure of homogeneity across these countries. Considering our entire set of European countries ($n_1 = N$), we can derive an aggregate measure of European homogeneity in consumer confidence at any given frequency. Alternatively, considering smaller subsets of countries ($n_1 < N$), we can assess the cohesion within a priori defined country segments. In line with Tellis et al. (2003), we could, for instance, assess to what extent the Scandinavian, Mediterranean, and Midwest segments of European countries are more homogeneous (i.e., have higher cohesion) than Europe as a whole, and if they do, at what frequencies (planning horizons).

In addition to an aggregate measure of cohesion *within* a set of time series, we can derive a measure of the cohesion *between* two distinct groups of time series. To that extent, we can

aggregate the dynamic correlations into a *cross-cohesion* index at frequency λ ,

$$\text{Cross - Coh}(\lambda) = \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=n_1+1}^{n_1+n_2} \rho_{x_i x_j}(\lambda), \quad (5)$$

which represents the co-movement between two distinct subsets of size n_1 and n_2 . In our specific setting, we could, for example, derive the cross-cohesion between the European countries and the United States to assess whether the evolution in the European countries' Consumer Confidence Indicator (CCI) is in sync with the evolution in the American Index of Consumer Sentiment (ICS).

The cohesion offers an aggregate measure of European homogeneity. However, there may be some variability among the different pairwise dynamic correlations, which raises the question of what factors drive the extent of correlation between two countries' CCI. As such, we can assess whether a larger geographical, economic, and/or cultural distance significantly decreases the resulting homogeneity in the respective countries' CCI. This analysis can be implemented for specific frequencies, in which case the $N(N-1)/2$ dynamic correlations at a given frequency could be regressed on the different distance measures. Alternatively, we could average the dynamic correlations in Eq. (3) over a prespecified frequency band $A = [\lambda_1, \lambda_2]$, with $0 \leq \lambda_1 < \lambda_2 \leq \pi$, as follows:

$$\rho_{x_i x_j}(A) = \frac{1}{(\lambda_2 - \lambda_1)} \int_{\lambda_1}^{\lambda_2} \rho_{x_i x_j}(\lambda) d\lambda. \quad (6)$$

The heterogeneity in CCI is then analyzed by computing this average dynamic correlation over a specified frequency band $[\lambda_1, \lambda_2]$, corresponding to a time interval (planning horizon) $[T_2, T_1]$, with $T_1 = (2\pi / \lambda_1)$ and $T_2 = (2\pi / \lambda_2)$. By properly selecting the frequency bands, this procedure allows inferences about the extent of European homogeneity across the short, medium, and long runs. The latter approach is less sensitive to the specific frequency selected and is conceptually similar to the method by Deleersnyder et al. (2004), who also consider jointly all frequencies in a certain frequency band (in their case, all frequencies corresponding to planning horizons between two and eight years). In practice, the integral in Eq. (6) is replaced by a sum over an equally spaced grid of λ -values in the interval $A = [\lambda_1, \lambda_2]$.

4. Data

We consider the Consumer Confidence Indicator in 14 European countries, namely, Austria (AU), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (GE), Greece (GR), Ireland (IE), Italy (IT), Portugal (PO), Spain (SP), Sweden (SE), The Netherlands (NL), and the United Kingdom (UK). Luxembourg is not included, as no data were collected for this country before 2002. The CCI is derived through consumer surveys collected by the European Commission and its member states in the framework of the Joint Harmonised EU Programme. Each month, more than 30,000 consumers are

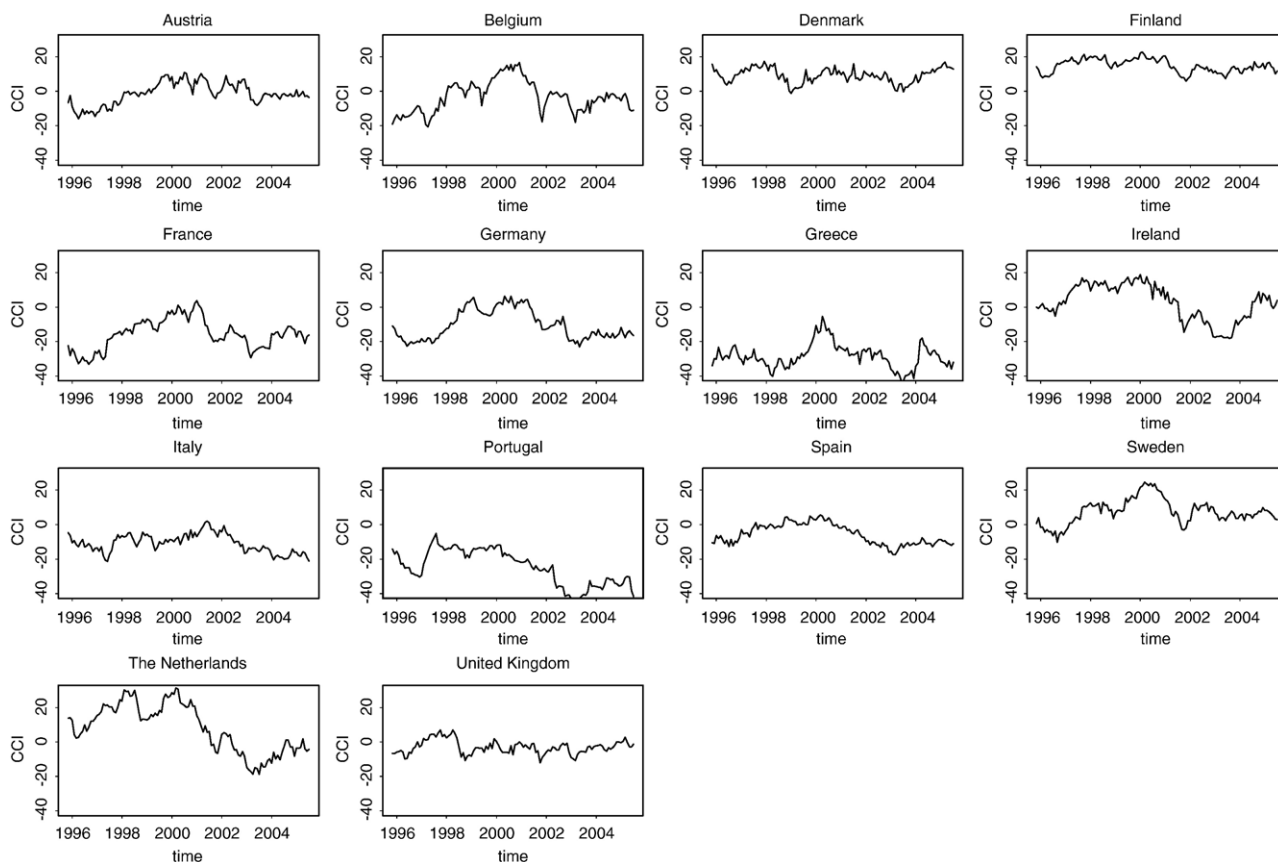


Fig. 3. The evolution of Consumer Confidence Indicators in Europe.

surveyed, and the CCI is computed as the arithmetic average of the balances (in percentage points) of answers pertaining to the financial situation of the households (“How do you expect the financial position of your household to change over the next twelve months?”), the general economic situation (“How do you expect the general economic situation in this country to develop over the next twelve months?”), savings (“Over the next twelve months, how likely is it that you save any money?”), and (with an inverted sign) unemployment expectations (“How do you expect the number of people unemployed in this country to change over the next twelve months?”). Respondents are asked whether they expect the variables of interest to increase, decrease, or remain stable over time. The decreases (in percentage points) are subsequently subtracted from the increases to obtain balance figures. A directional questionnaire is used, because directional changes have been found easier to predict than point values (Jonung, 1986). These balance data are seasonally adjusted by the data provider. Details on the derivation of the CCI are provided on the Web site of the Directorate General Economy and Finance (DG ECFIN) of the European Commission.⁴ Our series span the period from November 1995 – the entry date of Austria, Finland, and Sweden into the European Union – to July 2005 and therefore

result in 117 data points. The various CCI time series are depicted in Fig. 3.

Even though this construct has been used repeatedly in prior studies involving multiple countries (Golinelli & Parigi, 2004; Jansen & Nahuis, 2003; Nahuis & Jansen, 2004; Praet & Vuchelen, 1988, 1989; Vanden Abeele, 1983), none of these studies has formally investigated the level of cross-national equivalence of the measurement instrument, even though it has been emphasized (e.g., Nahuis & Jansen, 2004) that the surveys are harmonized by the European Commission, in that identical questionnaires with the same set of items are used in all countries. However, without access to the original, individual-level data, we cannot formally demonstrate that this harmonization ensures all forms of measurement invariance identified by Steenkamp and Baumgartner (1998). Still, it is possible to assess construct equivalence by investigating the nomological validity of the focal construct (Bagozzi, 1994). In this case, we examine whether, in different countries, the focal construct exhibits similar relations with other constructs with which it is theoretically predicted to be related. Support for such conceptual equivalence emerges because, in numerous countries, a similar relationship is reported with other variables, including GDP (see e.g., Berry & Davey, 2004; Golinelli & Parigi, 2004), changes in household consumption (Nahuis & Jansen, 2004), and stock returns (Jansen & Nahuis, 2003).

To allow for a formal comparison with the United States, we also obtained information about the American ICS over the same

⁴ http://europa.eu.int/comm/economy_finance/indicators/businessandconsumersurveys_en.htm.

time span. In line with Croux et al. (2001), we consider four regions within the United States: Northeast, Midwest, South, and West. Following the pioneering work of Katona (1951, 1979), the ICS has been used in numerous marketing studies, such as Allenby et al. (1996), Kamakura and Gessner (1986), and Kumar, Leone, and Gaskins (1995). Even though the European CCI and the American ICS are collected by two different institutions (i.e., the European Commission and the Survey Research Center at the University of Michigan), the wording of the various items is very similar.⁵ Moreover, relations similar to those for the CCI have been found with variables such as Gross Domestic Product (GDP) (Golinelli & Parigi, 2004), private consumption (Carroll, Fuhrer, & Wilcox, 1994; Epprih, Arguea, & Huth, 1998), and stock returns (Fisher & Statman, 2003). This finding supports the conceptual equivalence of the underlying constructs measured by both scales.

Finally, to study the cross-sectional variation in the pairwise dynamic correlations, we introduce various distance measures. Following Gielens and Dekimpe (2001), *geographical* proximity of countries *i* and *j* is operationalized as a dummy variable indicating whether two countries are contiguous. This variable takes the value of 0 when two countries are contiguous and 1 otherwise. In line with Mitra and Golder (2002), the *economic* distance between two countries is based on three dimensions: the difference in the countries' economic size (reflected in their Gross Domestic Product, GDP), economic prosperity (measured as their GDP per capita), and economic infrastructure (as reflected in the number of kilometers of railroad per square kilometer).⁶ A composite index of economic distance between two countries is subsequently formed on the basis of their squared differences along each of the three economic dimensions, following the procedure advocated by Kogut and Singh (1998). Relevant data were obtained from the World Factbook 2004.⁷ To conceptualize the *cultural* distance, we use the Schwartz national–culture framework (e.g., Schwartz, 1994; Schwartz & Ros, 1995), which has emerged as a major refinement and alternative to Hofstede's values (Steenkamp, 2001). Schwartz's framework is more recent and based on consumer, rather than organizational, values (Steenkamp, ter Hofstede, & Wedel, 1999), which renders it more applicable to the context of our study. Kogut and Singh's procedure is used again to derive a composite index of cultural distance on the basis of seven underlying dimensions: conservatism, intellectual autonomy, affective autonomy, hierarchy, egalitarianism, harmony, and mastery.

The relevant data to construct our measures of geographical, economic, and cultural distance are available for all considered

countries.⁸ As such, the regressions in Section 5.4 are implemented on 91 ($=14 \times 13/2$) observations. All distance measures are time invariant, because they are either intrinsically constant (geographical distance), not available as time-varying variables (cultural distance), or only collected at a higher level of temporal aggregation (economic distance) than the monthly CCI or ICS.

5. Results

The 14 European Consumer Confidence Indicator series result in 91 possible dynamic correlations. For illustrative purposes, we present in Section 5.1 the dynamic correlation among three key European countries: France, Germany, and the United Kingdom. Next, we derive an aggregate measure of the degree of homogeneity across the different member states through the cohesion index (Section 5.2) and compare this measure with (i) the cohesion in ICS across the four U.S. regions and (ii) the cross-cohesion between the United States and the European Union (Section 5.3). We subsequently assess whether there are certain clusters of countries that are relatively more homogeneous than the European Union as a whole. Finally, in Section 5.4, we assess whether the observed variability between the pairwise dynamic correlations is driven by the geographical, economic, and/or cultural distance between the respective countries and how this relative importance varies across different planning horizons.

5.1. Pairwise dynamic correlations

Rather than presenting all 91 dynamic correlations (which are available from the authors on request), we focus on the dynamic correlations between the CCI of three key countries: France, Germany, and the United Kingdom. France and Germany are often seen as key forces (both economically and politically) of European unification (The Economist, 2003). The United Kingdom, though also an important player, has been argued to have a rather distinct position, not only geographically but also in terms of economic integration and culture (Northcott, 1995).

In line with Jansen and Nahuis (2003), preliminary unit–root tests found the different CCI series to be integrated of order 1.⁹ The dynamic correlations were therefore computed on the first differences. For notational simplicity, we refer to these first-differenced series as CCIs. The corresponding dynamic correlations are presented in Fig. 4. On the bottom horizontal axis, we depict the frequency in radians, and the top axis presents the corresponding planning horizon (in months). As indicated previously, the higher the frequency, the lower the planning horizon. In all instances, the short-run dynamic correlation (corresponding to higher frequencies) is close to 0. This finding suggests that many disturbances that drive the high-frequency (monthly, bimonthly) fluctuations in consumer confidence are

⁵ For example, the question about the financial situation of the households is phrased as, "How do you expect the financial position of your household to change over the next 12 months?" in the CCI questionnaire and as "Do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?" in the ICS survey.

⁶ Mitra and Golder (2002) actually define a fourth economic variable, economic accessibility, operationalized as population density. Because this variable turns out to be highly correlated (0.707) with economic infrastructure in our setting, we exclude it from the analysis.

⁷ Available on the Web site of the CIA, <http://www.cia.gov/cia/publications/factbook/>.

⁸ Cultural data were obtained from Schwartz and Ros (1995) and personal communication with S.H. Schwartz.

⁹ Results are available from the authors on request.

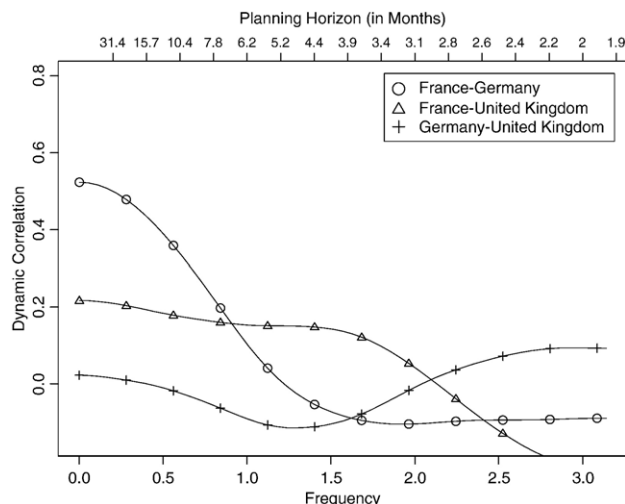


Fig. 4. The dynamic correlation for France, Germany, and the United Kingdom.

country specific and not correlated across respective countries. This short-run heterogeneity supports the idea of multi-domestic strategies. However, especially in the case of France and Germany, this view may be overly myopic, in that the dynamic correlation increases considerably as the planning horizon extends beyond six months. Market shocks that drive the longer-run evolution in consumers' confidence therefore have a similar impact in both countries, which supports a more integrated approach. The dynamic correlations with the United Kingdom, in contrast, remain considerably smaller at all frequencies. These findings, based on consumer perceptions, are in line with previous research by Lemmens, Croux, and Dekimpe (2005). In their pan-European study of the predictive content of managers' production expectations, they found significant cross-border effects between France and Germany, whereas the United Kingdom occupied a fairly isolated position.

Although we should be careful when generalizing from a limited number of cases, the preceding discussion already suggests little homogeneity in the short-run fluctuations in consumers' confidence. In terms of the longer-run movements, in contrast, there seems to be more variability across country pairs and a potential for identifying relatively homogeneous subsets. Finally, the observed differences seem related to the relative "closeness" of the different countries. Next, we investigate these preliminary patterns more formally.

5.2. European cohesion in consumer confidence

The first set of observations is confirmed by computing the European cohesion measure, which aggregates all 91 pairwise correlations. Fig. 5a presents the estimated cohesion, along with 90% bootstrap confidence bands.¹⁰ As indicated in Fig. 5a, European cohesion is very low at higher frequencies, suggesting

very little pan-European homogeneity in the short-run fluctuations in consumer confidence across the different member states. This finding implies that either country-specific shocks (e.g., local unemployment figures, the outcome of local elections) drive these short-run fluctuations or that different countries have different short-run reactions to common shocks (e.g., news issued by the European Central Bank, world events). Illustrating the former case, the closure of Renault's Belgian factory, announced in February 1997 (*The Economist*, 1997), caused a sharp fall in the Belgian CCI of seven points, while most other countries were unaffected. The common shock of September 11, 2001, affected the confidence in all member states considerably but in some countries (e.g., the British and Irish CCIs lost seven points that month) to a much larger extent than in others (e.g., the Nordic countries lost less than two points).¹¹

In line with the patterns observed for France and Germany, we further see that the cohesion increases somewhat as the planning horizon is extended, indicating a more homogeneous evolution once the dust has settled. To put the European cohesion levels in perspective, we compute as a benchmark the cohesion in the ICS (Index of Consumer Sentiment) across the four U.S. regions (see Fig. 5a).¹² A priori, we expect the latter cohesion to be considerably higher, if only because the United States has a much longer history of unification, shares a common language and currency, and has a single foreign policy and army. Across the entire range of frequencies, the U.S.-based cohesion exceeds its European counterpart. This difference is statistically significant for planning horizons beyond 3.4 months. Interestingly, at the higher frequencies, we see that also within the United States, there remains considerable heterogeneity in the behavior of the ICS. This finding is in line with the work of Wells and Reynolds (1979) and Hawkins, Roupe, and Coney (1981), who found significant geographical variation in consumer values, attitudes, and consumption across different regions of the United States, and that of Mittal, Kamakura, and Govind (2004), who found such differences in consumers' satisfaction with car dealers. However, because of the cross-sectional nature of their data, these previous studies do not allow inferences of increasing homogeneity over longer planning horizons.

When looking at the cross-cohesion between Europe and the different U.S. regions (see Fig. 5b), we find a comparable pattern, with higher correlations at lower frequencies. As the planning horizon extends, the European CCI and American ICS increasingly react in similar ways. Although this similarity may not seem too surprising given the United States' economic and political power in today's global marketplace (Julius, 2005), it is interesting to note that the cohesion within Europe does not significantly exceed the cross-cohesion level. That is, average correlations between pairs of European countries and between European countries and U.S. regions turn out to be of

¹⁰ Confidence bounds around the estimated (cross-)cohesion measures are computed using non-parametric block-bootstrap, as in Croux et al. (2001). An overview of bootstrap methods for time series can be found in Davison and Hinkley (2003). In our application, the block-bootstrap is implemented with blocks of minimum length 12, and standard errors are obtained from 1000 bootstrap replications of the cohesion measure.

¹¹ More details can be found in the "Employment in Europe 2001, Autumn Update" report of the European Commission, DG Employment and Social Affairs.

¹² The absence of ICS data at the state level precludes the derivation of a (cross-)cohesion measure for the 52 states of America.

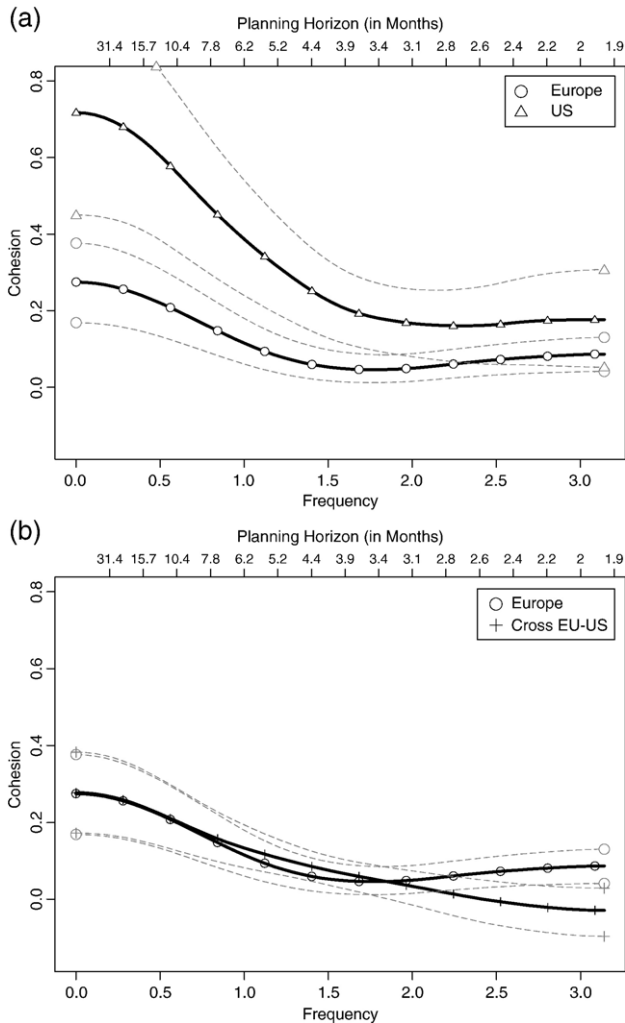


Fig. 5. The cohesion and cross-cohesion within and between Europe and the United States. (a) Cohesion within Europe and within the United States. (b) Cross-cohesion between Europe and United States and cohesion within Europe.

comparable magnitude, in particular in the medium and longer runs. As a potential reason, Europe and the United States are each other's main trading partners, both accounting for around one-fifth of the other's bilateral trade, a matter of €1 billion a day.¹³ Hence, recent political claims on Europe's distinctive (relative to the United States) identity are not yet fully reflected in its consumers' perceptions.

5.3. European segments

Because the overall cohesion across all 14 countries is fairly small, even at the lower frequencies, the question emerges: does this picture change when considering smaller subsets of countries? A few outlying countries may drive the overall homogeneity estimate down. From Figs. 4 and 5a, it is obvious that the European-based cohesion is considerably lower than the dynamic correlations reported between France and Germany. We could adopt several a priori segmentation schemes but

instead follow, for illustrative purposes, the typology adopted in Tellis et al. (2003) and define the following three segments: (i) Scandinavian (DK, FI, and SE), (ii) Mediterranean (FR, GR, IT, PO, and SP), and (iii) Midwest (AU, BE, GE, IE, NL, and UK).

As indicated in Fig. 6, the Scandinavian and Midwest countries in particular are characterized by considerably higher homogeneity at lower frequencies. Although not extremely high in absolute numbers, cohesion in longer planning horizons within the Scandinavian segment approaches the values obtained within the United States (i.e., confidence bands overlap for small frequencies) and is significantly higher than the cohesion obtained for the Mediterranean countries (i.e., confidence bands do not overlap for small frequencies).

The emergence of a rather homogeneous Scandinavian segment confirms previous findings by Kumar et al. (1998), Helsen, Jedidi, and DeSarbo (1993), and Tellis et al. (2003). Much less homogeneity is observed among the Mediterranean countries, irrespective of the time horizon considered. These findings are in line with Bijmolt et al. (2004) who, in their study of financial product ownership, identified relatively homogeneous segments among the Nordic and Midwest countries, while most Mediterranean countries formed single-country segments. Again, very little cohesion is observed in short planning horizons, irrespective of the country segment.

5.4. Does distance still matter?

The examples in Fig. 4 (for France, Germany, and the United Kingdom) suggest that there may be some variability in dynamic correlations across both different country pairs and different planning horizons. To assess this variability more formally, we regress the pairwise correlations on indicators of economic, geographical, and cultural distance for three different planning horizons, namely, the short, medium, and longer runs.

In marketing literature, no unique definition exists for what constitutes short, medium, and long runs (see the very different operationalizations advocated in Dekimpe & Hanssens, 1999; Mela, Gupta, & Lehmann, 1997). Because consumers' attitudes change quickly (Leone & Kamakura, 1983), sometimes causing

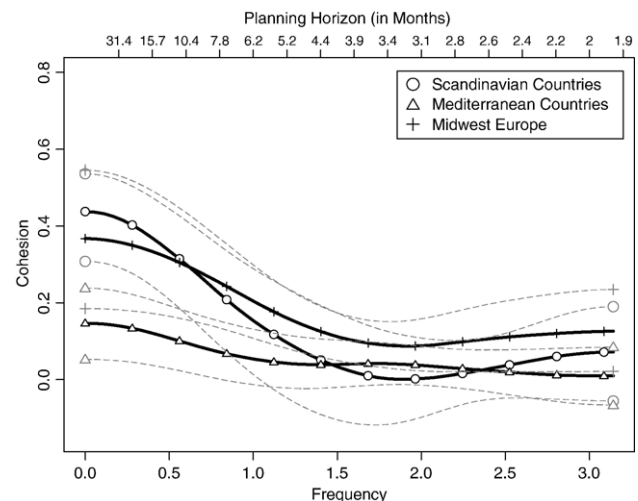


Fig. 6. The cohesion index in predefined market segments.

¹³ See the European Commission report, http://europa.eu.int/comm/trade/issues/bilateral/countries/usa/index_en.htm.

Table 2
OLS-estimated regression coefficients (and standard errors) of the drivers of variability among the dynamic correlations for different planning horizons

	Static correlation	Short run	Medium run	Long run
Geographical distance	−0.032 (0.036)	−0.008 (0.039)	−0.032 (0.040)	−0.059 (0.053)
Economic distance	−0.012 (0.008)	−0.012 (0.009)	−0.021** (0.009)	−0.029** (0.012)
Cultural distance	0.003 (0.011)	0.005 (0.012)	−0.019 (0.012)	−0.048*** (0.016)
Intercept	0.102** (0.039)	0.088** (0.042)	0.227*** (0.043)	0.457*** (0.058)
N=91				
Overall <i>F</i> -statistic, <i>p</i> -value	0.351	0.525	0.026**	0.001***
<i>R</i> ²	0.037	0.025	0.101	0.175
Adjusted <i>R</i> ²	0.004	−0.008	0.070	0.147

p*<0.100; *p*<0.050; ****p*<0.010.

them to use very short (monthly) planning horizons (Thaler, 1985), we define our short-run planning horizon as those fluctuations with a periodicity inferior to four months. This definition corresponds to a frequency band $A_1 = [\frac{\pi}{2}, \pi[$. The medium term is assumed to correspond to a planning horizon of four to twelve months, with a frequency band $A_2 = [\frac{\pi}{6}, \frac{\pi}{2}[$, and the longer-term fluctuations are assumed to correspond to cycles of twelve months to two years, or a frequency band $A_3 = [\frac{\pi}{12}, \frac{\pi}{6}[$. We do not take fluctuations of lower frequency into account to ensure a sufficient number of cycles for reliable analysis.¹⁴ As indicated in Section 2.3, we integrate the dynamic correlations over the different frequencies in a given frequency band to arrive at a single (average) estimate for the dynamic correlation in that band.

Three regression models are subsequently estimated; their dependent variables are the dynamic correlations in the short-, medium-, and long-run frequency bands, and their explanatory variables are the indicators for geographical, economic, and cultural distance. Fisher *z*-transforms are applied to the dynamic correlations, which are typically not normally distributed. Single-equation estimation techniques are used. A systems approach would not result in more efficient parameter estimates, because all equations contain the same set of explanatory variables. Preliminary White tests (available on request) do not reveal significant heteroskedasticity in any of the regressions. Because each observation in the regressions corresponds to a pair of countries, possible correlation among the error terms can be modeled by introducing random country effects, as in Sethuraman, Srinivasan, and Kim (1999). The latter, however, turned out to be unimportant.¹⁵ Hence, we stick to the ordinary least squares estimator. The results are reported in Table 2.

¹⁴ We observe nearly five cycles of two years in our sample. We also check the robustness of our results with modified spans of the short-, medium-, and long-run planning horizons. Our substantive results are not affected.

¹⁵ Farley and Lehmann (1986) note that the bias due to non-independence may not be serious if the percentage of non-zero correlations between pairs of error terms is relatively small. In our application, this ratio is about 15%. When we adopted a GLS approach to account for the aforementioned dependencies, qualitatively similar conclusions were obtained (detailed results available on request).

Remember that, in terms of the short-run correlations, very small values were obtained for each of the three country pairs in Fig. 4. This pattern was also found in the larger set of correlations. Not surprisingly, the short-run regression results in a very low (adjusted) *R*² of 0.025 (−0.008) and an insignificant overall *F*-statistic (*p*=0.525). Irrespective of geographical, economic, or cultural distance, the high-frequency fluctuations in two countries' CCI do not show much correlation. The low explanatory power of the distance measures could be driven in part by measurement error in the construct, which is unlikely to be systematically related to these distance measures but is picked up as short-run fluctuation.

The explanatory power of the cross-sectional regressions increases as one moves toward the lower frequency movements in CCIs. In the medium run, the (adjusted) *R*² increases to 0.101 (0.070), and then becomes 0.175 (0.147) in the long run. Also, the corresponding *F*-statistics become highly significant (*p*=0.026 and 0.001, respectively). In the medium run, the economic distance becomes significant (*p*<0.05), and in the long run, both the economic and cultural distance become significant (*p*<0.05 and 0.01, respectively). The correlation in longer-run CCI movements decreases as the economic distance becomes larger and as countries become more culturally different. No such insights could have been obtained from traditional static correlations, which result in a poorly fitting model (adjusted *R*²=0.004) with an insignificant *F*-statistic (*p*=0.351) and no significant distance measures.

6. Conclusions and discussion

Consumer sentiment seems “the sort of economics anyone can grasp” (BBC News Online, 2001). Not surprisingly, the release of Consumer Confidence Indicator (CCI) and Index of Consumer Sentiment (ICS) updates receives considerable coverage in both trade publications and the popular business press. As a consequence, managers are very much aware of any fluctuations in these confidence indices and take them into account when making inventory and production decisions (Chakrabarty, Chopin, & Darrat, 1998). Because consumers' confidence in their economic situation is linked to their propensity to buy and their future expenditures, their price and promotional sensitivity, and their inclination to buy private labels, updates about the evolution of a country's CCI (ICS) are key inputs for marketing managers as well.

Country segments identify countries whose customers “desire similar benefits and exhibit similar behaviors, thereby forming (relatively) homogenous segments such that there is heterogeneity across segments” (Bolton & Myers, 2003, p. 110). Key considerations in this respect are similarities in market potential and buying propensity (Kotabe & Helsen, 2001) and common responsiveness to marketing mix changes (Bolton & Myers, 2003). Given the aforementioned link between these characteristics and consumers' confidence, along with the public availability of these data across multiple countries, CCIs provide useful segmentation information. However, the traditional static correlations between different countries' CCI tend to be small (average correlation across all 14 countries of 0.112), suggesting

limited potential for pan-European strategies. Moreover, the correlation at high frequencies (corresponding to short planning horizons) is low and unrelated to the respective countries' geographical, economic, or cultural distance. Short-run movements in consumers' confidence are driven by country-specific shocks and/or differing reactions to common shocks. Based on such short-run considerations, managers may feel the need to develop country-specific strategies. However, such a myopic focus may underestimate potential cross-country similarities. Indeed, the cross-country correlations become more pronounced as the planning horizon is extended, a phenomenon that cannot be discerned with traditional (static) analyses. Moreover, these correlations tend to be higher as the economic and cultural distance becomes smaller, suggesting the appropriateness of regional marketing strategies.

As discussed in Bronnenberg et al. (2006), promotional prices tend to vary on a frequent basis, which makes them an appealing instrument to deal with short-run (often country-specific) changes in consumers' confidence and buying propensity. The planning horizon considered for regular price changes, in contrast, tends to be considerably longer. Country-specific differences then become much less pronounced, offering the potential for a cross-country harmonization of these regular price changes. Many brand-building activities require an even longer-run perspective (Lodish & Mela, 2006). As companies increasingly operate on pan-regional or even pan-European scales, the considerable increase in cross-country cohesion at very low frequencies (long planning horizons) can support common brand positioning across countries that are economically and culturally similar, even though a myopic focus on short-run success and cross-country differences may cause some managers to overlook this possibility (Lodish & Mela, 2006). Similarly, many European retailers have expanded the geographic scope of their operations beyond their home countries (Gielens & Dekimpe, 2001, 2007), which raises the question of whether customers in a new host market will have a similar propensity to buy private labels (Kumar & Steenkamp, 2007). Consumer confidence in the economy is a key driver of private-label success (Lamey et al., in press), which makes the increased cohesion over longer planning horizons of great interest to retailers operating in multiple European countries.

Our study has various limitations that offer avenues for further research. First, the managerial usefulness of our insights was demonstrated by building on prior research that supports the link between consumers' confidence and their buying intentions, expenditures, and price responsiveness. Future research might incorporate simultaneously CCI, performance, and marketing support series into one model, then directly compute the cohesion among these constructs at different planning horizons. Second, no individual-level data were available. If they had been available, we could have assessed the measurement invariance of the CCI across different countries in more depth, following the procedure outlined by Steenkamp and Baumgartner (1998). In addition, we could look for cross-national consumer segments and exploit both between- and within-country differences (Bijmolt et al., 2004). Moreover, because we only observe country-level series, the low-, medium-, and high-frequency components observed in aggregate series are actually a mixture of individual-level cycles.

An extension of the data augmentation procedures discussed by Chen and Yang (in press) and Musalem, Bradlow and Raju (in press), among others, to the current dynamic setting could result in interesting additional insights. Third, we focused on the CCI as a general basis for segmentation, because it has been shown to influence various aspects of consumers' behavior. However, it would be useful to assess the robustness of our substantive conclusions by considering cohesion among other (less general) constructs. For example, retailers and manufacturers of fast moving consumer goods may want to consider the cohesion in the Retail Trade Confidence Indicator across different European countries (Nahuis & Jansen, 2004), while for other sectors, cohesion in European Production Expectation surveys (e.g., Lemmens et al., 2005) may be of central interest. Fourth, we applied the cohesion concept to a priori determined segments, following the typology of Tellis et al. (2003). Researchers could also explore the homogeneity of other country combinations. Alternatively, they could attempt to identify the segments endogenously through, for example, overlapping or fuzzy cluster analysis (Wedel & Kamakura, 1998). More research is needed, however, about how the block-bootstrap procedure we used for our statistical inference might be adapted in such a setting. Fifth, we adopted a two-step approach, in that we first determined the dynamic correlations using a non-parametric estimation procedure, then regressed them on various distance measures. It would be useful but not trivial to explore the potential efficiency gains of a one-step procedure.

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